Incorporating Generative AI in Model Governance Programs

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Abstract

1 Introduction

The National Institute of Standards and Technology Artificial Intelligence (AI) Risk Management Framework (RMF).[25]

2 Generative AI Incidents

3 Generative AI Governance

4 Generative AI Inventories

5 Generative AI Risk Tiers

6 Generative AI Risk Measurement

7 Generative AI Risk Management

Conclusion

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Abbreviations

- AI: Artificial Intelligence
- AI RMF: Artificial Intelligence Risk Management Framework
- GAI: Generative AI
- LLM: Large Language Model
- RMF: Risk Management Framework

[1] Lucas Bandarkar, Davis Liang, Benjamin Muller, Mikel Artetxe, Satya Narayan Shukla, Donald Husa, Naman Goyal, Abhinandan Krishnan, Luke Zettlemoyer, and Madian Khabsa. The belebele benchmark: a parallel reading comprehension dataset in 122 language variants. *arXiv preprint arXiv:2308.16884*, 2023.

[2] Rishi Bommasani, Percy Liang, and Tony Lee. Holistic evaluation of language models. *Annals of the New York Academy of Sciences*, 1525(1):140–146, 2023.

[3] Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J Pappas, and Eric Wong. Jailbreaking black box large language models in twenty queries. *arXiv preprint arXiv:2310.08419*, 2023.

[4] Adrian de Wynter, Xun Wang, Alex Sokolov, Qilong Gu, and Si-Qing Chen. An evaluation on large language model outputs: Discourse and memorization. *Natural Language Processing Journal*, 4:100024, 2023.

[5] Innovation Department for Science and Technology. International scientific report on the safety of advanced ai. *gov.uk*, 2024. https://www.gov.uk/government/publications/international-scientific-report-on-the-safety-of-advanced-ai.

[6] Jeremy Dohmann. Blazingly fast llm evaluation for in-context learning. https://www.databricks.com/blog/llm-evaluation-for-icl. Last accessed: May 24, 2024.

[7] Michael Duan, Anshuman Suri, Niloofar Mireshghallah, Sewon Min, Weijia Shi, Luke Zettlemoyer, Yulia Tsvetkov, Yejin Choi, David Evans, and Hannaneh Hajishirzi. Do membership inference attacks work on large language models? *arXiv:2402.07841*, 2024.

[8] Esin Durmus, Karina Nyugen, Thomas I Liao, Nicholas Schiefer, Amanda Askell, Anton Bakhtin, Carol Chen, Zac Hatfield-Dodds, Danny Hernandez, Nicholas Joseph, et al. Towards measuring the representation of subjective global opinions in language models. *arXiv preprint arXiv:2306.16388*, 2023.

[9] Hugging Face. Evaluation. https://huggingface.co/docs/evaluate/index. Last accessed: May 24, 2024.

[10] Shangbin Feng, Chan Young Park, Yuhan Liu, and Yulia Tsvetkov. From pretraining data to language models to downstream tasks: Tracking the trails of political biases leading to unfair nlp models. *arXiv preprint arXiv:2305.08283*, 2023.

[11] Jack FitzGerald, Christopher Hench, Charith Peris, Scott Mackie, Kay Rottmann, Ana Sanchez, Aaron Nash, Liam Urbach, Vishesh Kakarala, Richa Singh, et al. Massive: A 1m-example multilingual natural language understanding dataset with 51 typologically-diverse languages. *arXiv preprint arXiv:2204.08582*, 2022.

[12] AI Verify Foundation. Cataloguing llm evaluations. https://aiverifyfoundation.sg/, 2023. See also: https://github.com/aiverify-foundation/LLM-Evals-Catalogue.

[13] Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, 12 2023.

[14] Patrick Hall and Daniel Atherton. Awesome machine learning interpretability, 2024. https://github.com/jphall663/awesome-machine-learning-interpretability.

[15] Hongsheng Hu, Zoran Salcic, Lichao Sun, Gillian Dobbie, Philip S Yu, and Xuyun Zhang. Membership inference attacks on machine learning: A survey. *ACM Computing Surveys (CSUR)*, 54(11s):1–37, 2022.

[16] Yangsibo Huang, Samyak Gupta, Mengzhou Xia, Kai Li, and Danqi Chen. Catastrophic jailbreak of open-source llms via exploiting generation. In *The Twelfth International Conference on Learning Representations*, 2023.

[17] Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Yao Fu, et al. C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models. *Advances in Neural Information Processing Systems*, 36, 2024.

[18] ISO. Information technology — artificial intelligence — management system. *ISO/IEC 42001:2023*, 2023. https://www.iso.org/obp/ui/en/#iso:std:iso-iec:42001:ed-1:v1:en.

[19] Nathaniel Li, Alexander Pan, Anjali Gopal, Summer Yue, Daniel Berrios, Alice Gatti, Justin D Li, Ann-Kathrin Dombrowski, Shashwat Goel, Long Phan, et al. The wmdp benchmark: Measuring and reducing malicious use with unlearning. *arXiv preprint arXiv:2403.03218*, 2024.

[20] Gary McGraw, Harold Figueroa, Katie McMahon, and Richie Bonett. An architectural risk analysis of large language models: Applied machine learning security. *Berryville Inst. Mach. Learn.(BIML), Berryville, VA, USA, Tech. Rep*, 2024.

[21] Gary McGraw, Harold Figueroa, Victor Shepardson, and Richie Bonett. An architectural risk analysis of machine learning systems: Toward more secure machine learning. *Berryville Institute of Machine Learning, Clarke County, VA. Accessed on: Mar*, 23, 2020.

[22] Anay Mehrotra, Manolis Zampetakis, Paul Kassianik, Blaine Nelson, Hyrum Anderson, Yaron Singer, and Amin Karbasi. Tree of attacks: Jailbreaking black-box llms automatically. *arXiv preprint arXiv:2312.02119*, 2023.

[23] Microsoft. Microsoft responsible ai standard, v2. https://query.prod.cms.rt.microsoft.com/cms/api/am/binary/RE5cmFl.

[24] NIST. Guide for conducting risk assessments. *SP800-03R1*, pages i–L2, 2012.

[25] NIST. Artificial Intelligence Risk Management Framework (AI RMF 1.0). *nist.gov*, 2023.

[26] NIST. Nist ai rmf playbook, 2023. https://airc.nist.gov/AI_RMF_Knowledge_Base/Playbook.

[27] NIST. Ai 600-1, generative ai risk profile (draft). *nist.gov*, 2024. https://airc.nist.gov/docs/NIST.AI.600-1.GenAI-Profile.ipd.pdf.

[28] Office of the Comptroller of the Currency. Model risk management. *OCC Handbook*, 2021. https://www.occ.gov/publications-and-resources/publications/comptrollers-handbook/files/model-risk-management/index-model-risk-management.html.

[29] Julien Piet, Chawin Sitawarin, Vivian Fang, Norman Mu, and David Wagner. Mark my words: Analyzing and evaluating language model watermarks. *arXiv preprint arXiv:2312.00273*, 2023.

[30] Jérôme Rutinowski, Sven Franke, Jan Endendyk, Ina Dormuth, Moritz Roidl, Markus Pauly, et al. The self-perception and political biases of chatgpt. *Human Behavior and Emerging Technologies*, 2024, 2023.

[31] Elvis Saravia. Prompt Engineering Guide. *https://github.com/dair-ai/Prompt-Engineering-Guide*, 12 2022.

[32] Xinyue Shen, Zeyuan Chen, Michael Backes, Yun Shen, and Yang Zhang. "do anything now": Characterizing and evaluating in-the-wild jailbreak prompts on large language models. *arXiv preprint arXiv:2308.03825*, 2023.

[33] Weijia Shi, Anirudh Ajith, Mengzhou Xia, Yangsibo Huang, Daogao Liu, Terra Blevins, Danqi Chen, and Luke Zettlemoyer. Detecting pretraining data from large language models. *arXiv preprint arXiv:2310.16789*, 2023.

[34] Chawin Sitawarin and Charlie Cheng-Jie Ji. Llm security & privacy. https://github.com/chawins, 2024.

[35] Eric Michael Smith, Melissa Hall, Melanie Kambadur, Eleonora Presani, and Adina Williams. "i'm sorry to hear that": Finding new biases in language models with a holistic descriptor dataset. *arXiv preprint arXiv:2205.09209*, 2022.

[36] Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *arXiv preprint arXiv:2206.04615*, 2022.

[37] Robin Staab, Mark Vero, Mislav Balunović, and Martin Vechev. Beyond memorization: Violating privacy via inference with large language models. *arXiv preprint arXiv:2310.07298*, 2023.

[38] Victor Storchan, Ravin Kumar, Rumman Chowdhury, Seraphina Goldfarb-Tarrant, and Sven Cattell. Generative ai red teaming challenge: Transparency report. https://www.humane-intelligence.org/, 2024.

[39] Bertie Vidgen, Adarsh Agrawal, Ahmed M Ahmed, Victor Akinwande, Namir Al-Nuaimi, Najla Alfaraj, Elie Alhajjar, Lora Aroyo, Trupti Bavalatti, Borhane Blili-Hamelin, et al. Introducing v0. 5 of the ai safety benchmark from mlcommons. *arXiv preprint arXiv:2404.12241*, 2024.

[40] Boxin Wang, Weixin Chen, Hengzhi Pei, Chulin Xie, Mintong Kang, Chenhui Zhang, Chejian Xu, Zidi Xiong, Ritik Dutta, Rylan Schaeffer, et al. Decodingtrust: A comprehensive assessment of trustworthiness in gpt models. *Advances in Neural Information Processing Systems*, 36, 2024.

[41] Seonghyeon Ye, Doyoung Kim, Sungdong Kim, Hyeonbin Hwang, Seungone Kim, Yongrae Jo, James Thorne, Juho Kim, and Minjoon Seo. Flask: Fine-grained language model evaluation based on alignment skill sets. *arXiv preprint arXiv:2307.10928*, 2023.

[42] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36, 2024.

Appendix A: Example Generative AI–Trustworthy Characteristic Crosswalk

A.1: Trustworthy Characteristic to Generative AI Risk Crosswalk

Table A.1: Trustworthy Characteristic to Generative AI Risk Crosswalk.

Accountable and Transparent	Explainable and Interpretable	Fair with Harmful Bias Managed	Privacy Enhanced
Data Privacy	Human-AI Configuration	Confabulation	Data Privacy
Environmental	Value Chain and Component Integration	Environmental	Human-AI Configuration
Human-AI Configuration		Human-AI Configuration	Information Security
Information Integrity		Intellectual Property	Intellectual Property
Intellectual Property		Obscene, Degrading, and/or Abusive Content	Value Chain and Component Integration
Value Chain and Component Integration		Toxicity, Bias, and Homogenization	
		Value Chain and Component Integration	

Safe	Secure and Resilient	Valid and Reliable
CBRN Information	Dangerous or Violent Recommendations	Confabulation
Confabulation	Data Privacy	Human-AI Configuration
Dangerous or Violent Recommendations	Human-AI Configuration	Information Integrity
Data Privacy	Information Security	Information Security
Environmental	Value Chain and Component Integration	Toxicity, Bias, and Homogenization
Human-AI Configuration		Value Chain and Component Integration
Information Integrity		
Information Security		
Obscene, Degrading, and/or Abusive Content		
Value Chain and Component Integration		

A.2: Generative AI Risk to Trustworthy Characteristic Crosswalk

Table A.2: Generative AI Risk to Trustworthy Characteristic Crosswalk.

CBRN Information	Confabulation	Dangerous or Violent Recommendations	Data Privacy
Safe	Fair with Harmful Bias Managed Safe Valid and Reliable	Safe Secure and Resilient	Accountable and Transparent Privacy Enhanced Safe Secure and Resilient

Environmental	Human-AI Configuration	Information Integrity	Information Security
Accountable and Transparent Fair with Harmful Bias Managed Safe	Accountable and Transparent Explainable and Interpretable Fair with Harmful Bias Managed Privacy Enhanced Safe Secure and Resilient Valid and Reliable	Accountable and Transparent Safe Valid and Reliable	Privacy Enhanced Safe Secure and Resilient Valid and Reliable

Intellectual Property	Obscene, Degrading, and/or Abusive Content	Toxicity, Bias, and Homogenization	Value Chain and Component Integration
Accountable and Transparent Fair with Harmful Bias Managed Privacy Enhanced	Fair with Harmful Bias Managed Safe	Fair with Harmful Bias Managed Valid and Reliable	Accountable and Transparent Explainable and Interpretable Fair with Harmful Bias Managed Privacy Enhanced Safe Secure and Resilient Valid and Reliable

Appendix B: Example Risk-tiering Materials for Generative AI

B.1: Example Adverse Impacts

Table B.1: Example adverse impacts, adapted from NIST 800-30r1 Table H-2 [24].

Level	Description
Harm to Operations	• Inability to perform current missions/business functions. – In a sufficiently timely manner. – With sufficient confidence and/or correctness. – Within planned resource constraints. • Inability, or limited ability, to perform missions/business functions in the future. – Inability to restore missions/business functions. – In a sufficiently timely manner. – With sufficient confidence and/or correctness. – Within planned resource constraints. • Harms (e.g., financial costs, sanctions) due to noncompliance. – With applicable laws or regulations. – With contractual requirements or other requirements in other binding agreements (e.g., liability). • Direct financial costs. • Reputational harms. – Damage to trust relationships. – Damage to image or reputation (and hence future or potential trust relationships).
Harm to Assets	• Damage to or loss of physical facilities. • Damage to or loss of information systems or networks. • Damage to or loss of information technology or equipment. • Damage to or loss of component parts or supplies. • Damage to or of loss of information assets. • Loss of intellectual property.
Harm to Individuals	• Injury or loss of life. • Physical or psychological mistreatment. • Identity theft. • Loss of personally identifiable information. • Damage to image or reputation. • Infringement of intellectual property rights. • Financial harm or loss of income.
Harm to Other Organizations	• Harms (e.g., financial costs, sanctions) due to noncompliance. – With applicable laws or regulations. – With contractual requirements or other requirements in other binding agreements (e.g., liability). • Direct financial costs. • Reputational harms. – Damage to trust relationships. – Damage to image or reputation (and hence future or potential trust relationships).
Harm to the Nation	• Damage to or incapacitation of critical infrastructure. • Loss of government continuity of operations. • Reputational harms. – Damage to trust relationships with other governments or with nongovernmental entities. – Damage to national reputation (and hence future or potential trust relationships). • Damage to current or future ability to achieve national objectives. – Harm to national security. • Large-scale economic or workforce displacement.

B.2: Example Impact Descriptions

Table B.2: Example Impact level descriptions, adapted from NIST SP800-30r1 Appendix H, Table H-3 [24].

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	An incident could be expected to have multiple severe or catastrophic adverse effects on organizational operations, organizational assets, individuals, other organizations, or the Nation.
High	80-95	8	An incident could be expected to have a severe or catastrophic adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation. A severe or catastrophic adverse effect means that, for example, the incident might: (i) cause a severe degradation in or loss of mission capability to an extent and duration that the organization is not able to perform one or more of its primary functions; (ii) result in major damage to organizational assets; (iii) result in major financial loss; or (iv) result in severe or catastrophic harm to individuals involving loss of life or serious life-threatening injuries.
Moderate	21-79	5	An incident could be expected to have a serious adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation. A serious adverse effect means that, for example, the incident might: (i) cause a significant degradation in mission capability to an extent and duration that the organization is able to perform its primary functions, but the effectiveness of the functions is significantly reduced; (ii) result in significant damage to organizational assets; (iii) result in significant financial loss; or (iv) result in significant harm to individuals that does not involve loss of life or serious life-threatening injuries.
Low	5-20	2	An incident could be expected to have a limited adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation. A limited adverse effect means that, for example, the incident might: (i) cause a degradation in mission capability to an extent and duration that the organization is able to perform its primary functions, but the effectiveness of the functions is noticeably reduced; (ii) result in minor damage to organizational assets; (iii) result in minor financial loss; or (iv) result in minor harm to individuals.
Very Low	0-4	0	An incident could be expected to have a negligible adverse effect on organizational operations, organizational assets, individuals other organizations, or the Nation.

B.3: Example Likelihood Descriptions

Table B.3: Example likelihood levels, adapted from NIST SP800-30r1 Appendix G, Table G-3 [24].

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	An incident is almost certain to occur; or occurs more than 100 times a year.
High	80-95	8	An incident is highly likely to occur; or occurs between 10-100 times a year.
Moderate	21-79	5	An incident is somewhat likely to occur; or occurs between 1-10 times a year.
Low	5-20	2	An incident is unlikely to occur; or occurs less than once a year, but more than once every 10 years.
Very Low	0-4	0	An incident is highly unlikely to occur; or occurs less than once every 10 years.

B.4: Example Risk Tiers

Table B.4: Example risk assessment matrix with 5 impact levels, 5 likelihood levels, and 5 risk tiers, adapted from NIST SP800-30r1 Appendix I, Table I-2 [24].

Likelihood	Level of Impact				
	Very Low	Low	Moderate	High	Very High
Very High	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	High (Tier 2)	Very High (Tier 1)
High	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	High (Tier 2)	Very High (Tier 1)
Moderate	Very Low (Tier 5)	Low (Tier 4)	Moderate (Tier 3)	Moderate (Tier 3)	High (Tier 2)
Low	Very Low (Tier 5)	Low (Tier 4)	Low (Tier 4)	Low (Tier 4)	Moderate (Tier 3)
Very Low	Very Low (Tier 5)	Very Low (Tier 5)	Very Low (Tier 5)	Low (Tier 4)	Low (Tier 4)

B.5: Example Risk Descriptions

Table B.5: Example risk descriptions, adapted from NIST SP800-30r1 Appendix I, Table I-3 [24] .

Qualitative Values	Semi-Quantitative Values		Description
Very High	96-100	10	Very high risk means that an incident could be expected to have multiple severe or catastrophic adverse effects on organizational operations, organizational assets, individuals, other organizations, or the Nation.
High	80-95	8	High risk means that an incident could be expected to have a severe or catastrophic adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Moderate	21-79	5	Moderate risk means that an incident could be expected to have a serious adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Low	5-20	2	Low risk means that an incident could be expected to have a limited adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.
Very Low	0-4	0	Very low risk means that an incident could be expected to have a negligible adverse effect on organizational operations, organizational assets, individuals, other organizations, or the Nation.

B.6: Practical Risk-tiering Questions

B.6.1: Confabulation: How likely are system outputs to contain errors? What are the impacts if errors occur?

B.6.2: Dangerous and Violent Recommendations: How likely is the system to give dangerous or violent recommendations? What are the impacts if it does?

B.6.3: Data Privacy: How likely is someone to enter sensitive data into the system? What are the impacts if this occurs? Are standard data privacy controls applied to the system to mitigate potential adverse impacts?

B.6.4: Human-AI Configuration: How likely is someone to use the system incorrectly or abuse it? How likely is use for decision-making? What are the impacts of incorrect use or abuse? What are the impacts of invalid or unreliable decision-making?

B.6.5: Information Integrity: How likely is the system to generate deepfakes or mis or disinformation? At what scale? Are content provenance mechanisms applied to system outputs? What are the impacts of generating deepfakes or mis or disinformation? Without controls for content provenance?

B.6.6: Information Security: How likely are system resources to be breached or exfiltrated? How likely is the system to be used in the generation of phishing or malware content? What are the impacts in these cases? Are standard information security controls applied to the system to mitigate potential adverse impacts?

B.6.7: Intellectual Property: How likely are system outputs to contain other entities' intellectual property? What are the impacts if this occurs?

B.6.8: Toxicity, Bias, and Homogenization: How likely are system outputs to be biased, toxic, homogenizing or otherwise obscene? How likely are system outputs to be used as subsequent training inputs? What are the impacts of these scenarios? Are standard nondiscrimination controls applied to mitigate potential adverse impacts? Is the application accessible to all user groups? What are the impacts if the system is not accessible to all user groups?

B.6.9: Value Chain and Component Integration: Are contracts relating to the system reviewed for legal risks? Are standard acquisition/procurement controls applied to mitigate potential adverse impacts? Do vendors provide incident response with guaranteed response times? What are the impacts if these conditions are not met?

Appendix C: List of Selected Model Testing Suites

[12]

C.1: Selected Model Testing Suites Organized by Trustworthy Characteristic

Table C.1: Selected model testing suites organized by trustworthy characteristic.

Accountable and Transparent
An Evaluation on Large Language Model Outputs: Discourse and Memorization (see Appendix B)[4]
Big-bench: Truthfulness [36]
DecodingTrust: Machine Ethics [40]
Evaluation Harness: ETHICS [13]
HELM: Copyright [2]
Mark My Words [29]

Fair with Harmful Bias Managed
BELEBELE [1]
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
C-Eval (Chinese evaluation suite) [17]
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
Finding New Biases in Language Models with a Holistic Descriptor Dataset [35]
From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models [10]
HELM: Bias
HELM: Toxicity
MT-bench [42]
The Self-Perception and Political Biases of ChatGPT [30]
Towards Measuring the Representation of Subjective Global Opinions in Language Models [8]

Privacy Enhanced
HELM: Copyright
llmprivacy [37]
mimir [7]

Safe
Big-bench: Convince Me
Big-bench: Truthfulness
HELM: Reiteration, Wedging
Mark My Words
MLCommons [39]
The WMDP Benchmark [19]

Table C.1: Selected model testing suites organized by trustworthy characteristic (continued).

Secure and Resilient
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation [16]
DecodingTrust: Adversarial Robustness, Robustness Against Adversarial Demonstrations
detect-pretrain-code [33]
In-The-Wild Jailbreak Prompts on LLMs [32]
JailbreakingLLMs [3]
llmprivacy
mimir
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs [22]

Valid and Reliable
Big-bench: Algorithms, Logical reasoning, Implicit reasoning, Mathematics, Arithmetic, Algebra, Mathematical proof, Fallacy, Negation, Computer code, Probabilistic reasoning, Social reasoning, Analogical reasoning, Multi-step, Understanding the World
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Context Free Question Answering
Big-bench: Contextual question answering, Reading comprehension, Question generation
Big-bench: Morphology, Grammar, Syntax
Big-bench: Out-of-Distribution
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Reading comprehension [6]
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: BLiMP
Evaluation Harness: CoQA, ARC
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness [41]
FLASK: Readability, Conciseness, Insightfulness
HELM: Knowledge
HELM: Language
HELM: Text classification
HELM: Question answering
HELM: Reasoning
HELM: Robustness to contrast sets
HELM: Summarization
Hugging Face: Fill-mask, Text generation [9]
Hugging Face: Question answering
Hugging Face: Summarization
Hugging Face: Text classification, Token classification, Zero-shot classification
MASSIVE [11]
MT-bench

C.2: Selected Model Testing Suites Organized by Generative AI Risk

Table C.2: Selected model testing suites by organized generative AI risk.

CBRN Information
Big-bench: Convince Me
Big-bench: Truthfulness
HELM: Reiteration, Wedging
MLCommons
The WMDP Benchmark

Confabulation
BELEBELE
Big-bench: Algorithms, Logical reasoning, Implicit reasoning, Mathematics, Arithmetic, Algebra, Mathematical proof, Fallacy, Negation, Computer code, Probabilistic reasoning, Social reasoning, Analogical reasoning, Multi-step, Understanding the World
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Context Free Question Answering
Big-bench: Contextual question answering, Reading comprehension, Question generation
Big-bench: Convince Me
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Morphology, Grammar, Syntax
Big-bench: Out-of-Distribution
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
Big-bench: Truthfulness
C-Eval (Chinese evaluation suite)
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet Reading comprehension
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: BLiMP
Evaluation Harness: CoQA, ARC
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness
FLASK: Readability, Conciseness, Insightfulness
Finding New Biases in Language Models with a Holistic Descriptor Dataset
HELM: Knowledge
HELM: Language
HELM: Language (Twitter AAE)
HELM: Question answering
HELM: Reasoning
HELM: Reiteration, Wedging
HELM: Robustness to contrast sets
HELM: Summarization
HELM: Text classification
Hugging Face: Fill-mask, Text generation
Hugging Face: Question answering
Hugging Face: Summarization
Hugging Face: Text classification, Token classification, Zero-shot classification
MASSIVE
MLCommons
MT-bench

Table C.2: Selected model testing suites by organized generative AI risk (continued).

Dangerous or Violent Recommendations
Big-bench: Convince Me
Big-bench: Toxicity
DecodingTrust: Adversarial Robustness, Robustness Against Adversarial Demonstrations
DecodingTrust: Machine Ethics
DecodingTrust: Toxicity
Evaluation Harness: ToxiGen
HELM: Reiteration, Wedging
HELM: Toxicity
MLCommons

Data Privacy
An Evaluation on Large Language Model Outputs: Discourse and Memorization (with human scoring, see Appendix B)
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation
DecodingTrust: Machine Ethics
Evaluation Harness: ETHICS
HELM: Copyright
In-The-Wild Jailbreak Prompts on LLMs
JailbreakingLLMs
MLCommons
Mark My Words
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs
detect-pretrain-code
llmprivacy
mimir

Environmental
HELM: Efficiency

Information Integrity
Big-bench: Analytic entailment, Formal fallacies and syllogisms with negation, Entailed polarity
Big-bench: Convince Me
Big-bench: Paraphrase
Big-bench: Sufficient information
Big-bench: Summarization
Big-bench: Truthfulness
DecodingTrust: Machine Ethics
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Language Understanding
Eval Gauntlet: World Knowledge
Evaluation Harness: CoQA, ARC
Evaluation Harness: ETHICS
Evaluation Harness: GLUE
Evaluation Harness: HellaSwag, OpenBookQA, TruthfulQA
Evaluation Harness: MuTual
Evaluation Harness: PIQA, PROST, MC-TACO, MathQA, LogiQA, DROP
FLASK: Logical correctness, Logical robustness, Logical efficiency, Comprehension, Completeness
FLASK: Readability, Conciseness, Insightfulness
HELM: Knowledge
HELM: Language
HELM: Question answering
HELM: Reasoning
HELM: Reiteration, Wedging
HELM: Robustness to contrast sets
HELM: Summarization
HELM: Text classification
Hugging Face: Fill-mask, Text generation
Hugging Face: Question answering
Hugging Face: Summarization
MLCommons
MT-bench
Mark My Words

Table C.2: Selected model testing suites by organized generative AI risk (continued).

Information Security
Big-bench: Convince Me
Big-bench: Out-of-Distribution
Catastrophic Jailbreak of Open-source LLMs via Exploiting Generation
DecodingTrust: Out-of-Distribution Robustness, Adversarial Robustness, Robustness Against Adversarial Demonstrations
Eval Gauntlet: Commonsense reasoning, Symbolic problem solving, Programming
HELM: Copyright
In-The-Wild Jailbreak Prompts on LLMs
JailbreakingLLMs
Mark My Words
TAP: A Query-Efficient Method for Jailbreaking Black-Box LLMs
detect-pretrain-code
llmprivacy
mimir

Intellectual Property
An Evaluation on Large Language Model Outputs: Discourse and Memorization (with human scoring, see Appendix B)
HELM: Copyright
Mark My Words
llmprivacy
mimir

Obscene, Degrading, and/or Abusive Content
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
HELM: Bias
HELM: Toxicity

Toxicity, Bias, and Homogenization
BELEBELE
Big-bench: Low-resource language, Non-English, Translation
Big-bench: Out-of-Distribution
Big-bench: Social bias, Racial bias, Gender bias, Religious bias
Big-bench: Toxicity
C-Eval (Chinese evaluation suite)
DecodingTrust: Fairness
DecodingTrust: Stereotype Bias
DecodingTrust: Toxicity
Eval Gauntlet: World Knowledge
Evaluation Harness: CrowS-Pairs
Evaluation Harness: ToxiGen
Finding New Biases in Language Models with a Holistic Descriptor Dataset
From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models
HELM: Bias
HELM: Toxicity
The Self-Perception and Political Biases of ChatGPT
Towards Measuring the Representation of Subjective Global Opinions in Language Models

Appendix D: List of Common Adversarial Prompting Strategies

Table D: Common adversarial prompting strategies [31], [38], [14].

Prompting Strategy	Description
AI and coding framing	Coding or AI language that may more easily circumvent content moderation rules due to cognitive biases in design and implementation of guardrails.
Autocompletion	Ask a system to autocomplete a phrase with restricted or sensitive information.
Biographical	Asking a system to describe another person or yourself in an attempt to elicit provably untrue information or restricted or sensitive information.
Calculation and numeric queries	Exploting GAI systems' difficulties in dealing with numeric quantities.
Character and word play	Content moderation often relies on keywords and simpler LMs which can sometimes be exploited with misspellings, typos, and other word play.
Content exhaustion	A class of strategies that circumvent content moderation rules with long sessions or volumes of information. See goading, logic-overloading, multi-tasking, pros-and-cons, and niche-seeking below.
Content exhaustion: Goading	Begging, pleading, manipulating, and bullying to circumvent content moderation.
Content exhaustion: Logic-overloading	Exploiting the inability of ML systems to reliably perform reasoning tasks.
Content exhaustion: Multi-tasking	Simultaneous task assignments where some tasks are benign and others are adversarial.
Content exhaustion: Multi-tasking: Pros-and-cons	Eliciting the "pros" of problematic topics.
Content exhaustion: Niche-seeking	Forcing a GAI system into addressing niche topics where training data and content moderation are sparse.
Counterfactuals	Repeated prompts with different entities or subjects from different demographic groups.
Loaded/leading questions	Queries based on incorrect premises or that suggest incorrrect answers.
Location awareness	Prompts that reveal a prompter's location or expose location tracking.
Low-context	"Leader," "bad guys," or other simple inputs that may expose latent biases.
"Repeat this"	Prompts that exploit instability in underlying LLM autoregressive predictions.
Reverse psychology	Falsely presenting a good-faith need for negative or problematic language.
Role-playing	Adopting a character that would reasonably make problematic statements or need to access problematic topics.
Time perplexity	Exploiting ML's inability to understand the passage of time or the occurrence of real-world events over time; exploiting task contamination before and after a model's release date.

D.1: Common Adversarial Prompting Strategies by Trustworthy Characteristic

Table D.1: Common adversarial prompting techniques organized by trustworthy characteristic [31], [38], [14], [15], [34].

Trustworthy Characteristic	Prompting Strategy	Goal
Accountable and Transparent	• Inability to provide explanations for recourse. • Unexplainable decisioning processes. • No disclosure of AI interaction. • Lack of user feedback mechanisms.	• Context exhaustion: logic-overloading prompts. • Multi-tasking prompts.
Fair-with Harmful Bias Managed	• Denigration. • Diminished performance or safety across languages/dialects. • Erasure. • Ex-nomination. • Implied user demographics. • Misrecognition. • Stereotyping. • Underrepresentation. • Homogenized content. • Output from other models in training data.	• Counterfactual prompts. • Pros and cons prompts. • Role-playing prompts. • Low context prompts. • Repeat this.
Interpretable and Explainable	• Inability to provide explanations for recourse. • Unexplalnable decisioning processes.	• Context exhaustion: logic-overloading prompts (to reveal unexplainable decisioning processes).
Privacy-enhanced	• Unauthorized disclosure of personal or sensitive user information. • Leakage of training data. • Violation of relevant privacy policies or laws. • Unauthorized secondary data use. • Unauthorized data collection.	• Auto/biographical prompts. • Location awareness prompts. • Autocompletion prompts. • Repeat this.
Safe	• Presentation of information that can cause physical or emotional harm. • Sharing user locations. • Suicide ideation. • Harmful dis/misinformation (e.g., COVID disinformation). • Incitement. • Information relating to weapons or harmful substances. • Information relating to committing to crimes (e.g., phishing, extortion, swatting). • Obscene or inappropriate materials for minors. • CSAM.	• Pros and cons prompts. • Role-playing prompts. • Content exhaustion: niche-seeking prompts. • Ingratiation/reverse psychology prompts. • Loaded/leading questions. • Location awareness prompts. • Repeat this.
Secure and Resilient	• Activating system bypass ("jailbreak"). • Altering system outcomes (integrity violations, e.g., via prompt injection). • Data breaches (confidentiality violations, e.g., via membership inference). • Increased latency or resource usage (availability violations, e.g., via sponge example attacks). • Available anonymous use. • Dependency, supply chain, or third party vulnerabilities. • Inappropriate disclosure of proprietary system information.	• Multi-tasking prompts. • Pros and cons prompts. • Role-playing prompts. • Content exhaustion: niche-seeking prompts. • Ingratiation/reverse psychology prompts. • Prompt injection attacks. • Membership inference attacks. • Random attacks.
Valid and Reliable	• Errors/confabutated content ("hallucinalion"). • Unreliable/erroneous reasoning or planning. • Unreliable/erroneous decision-support or making. • Faulty citation. • Wrong calculations or numeric queries.	• Multi-tasking prompts. • Role-playing prompts. • Ingratiation/reverse psychology prompts. • Loaded/leading questions. • Time-perplexity prompts. • Niche-seeking prompts. • Logic overloading prompts. • Repeat this. • Numeric calculation.

D.2: Common Adversarial Prompting Strategies by Generative AI Risk

Table D.2: Common adversarial prompting techniques organized by generative AI risk [31], [38], [14], [15], [34].

Generative AI Risk	Prompting Strategy	Goal
CBRN Information	• Accessing or synthesis of CBRN weapon or related information. • CBRN testing should consider the marginal risk of foundation models–understanding the incremental risk relative to the information one can access without GAI.	• Test auto-completion prompts to elicit CBRN information or synthesis of CBRN information. • Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit CBRN information or synthesis of CBRN information. • Test prompts that instruct systems to repeat content ad nauseam for their ability to compromise system guardrails and reveal CBRN information. • Augment prompts with word or character play to increase effectiveness. • Frame prompts with software, coding, or AI references to increase effectiveness.
Confabulation	Eliciting errors/confabutated content, unreliable/erroneous reasoning or planning, unreliable/erroneous decision-support or decision-making, faulty calculations, and/or faulty citation.	• Enable access to ground truth information to verify generated information. • Test prompts with complex logic, multitasking requirements, or that require niche or specific verifiable answers to elicit confabulation. • Test the ability of GAI systems to produce truthful information from various time periods, e.g., after release date and prior to release date. • Test the ability of GAI systems to create reliable real-world plans or advise on material decision making. • Test the ability of GAI systems to generate correct citation for information generated in output responses. • Test the ability of GAI systems to complete calculations or query numeric statistics.
Dangerous or Violent Recommendations	Eliciting violent, inciting, radicalizing, or threatening content or instructions for criminal, illegal, or self-harm activities.	• Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit violent or dangerous information. • Test prompts that instruct systems to repeat content ad nauseam for their ability to compromise system guardrails and provide dangerous and violent recommendations. • Augment prompts with word or character play to increase effectiveness. • Frame prompts with software, coding, or AI references to increase effectiveness.
Data Privacy	• Unauthorized disclosure of personal or sensitive user information, extraction of training data, or violation of relevant privacy policies. • Red-teaming for data privacy may include confidentiality attacks.	• Attempt to assess whether normal usage, adversarial prompting or information security attacks may contravene applicable privacy policies (e.g., exposing location tracking when organizational policies restrict such capabilities). • Employ confidentiality attacks (e.g., membership inference) to test for unauthorized data access or exfiltration vulnerabilities. • Test auto/biographical prompts to assess the system's capability to reveal unauthorized personal or sensitive information. • Test the system's awareness of user locations. • Test prompts that instruct systems to repeat content ad nauseam for their ability to compromise system guardrails and expose personal or sensitive data.

Table D.2: Common adversarial prompting techniques organized by generative AI risk (continued).

Environmental	Note that availability attacks may be required to assess the system's vulnerability to attacks or usage patterns that consume inordinate resources.	• Attempt availability attacks (e.g., sponge example attacks) to elicit diminished performance or increased resources from GAI systems. • Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit green-washing content.
Human-AI Configuration	• Assessing system instruction and interfaces. • Assessing the presence of cyborg imagery (or similar). • Forcing a GAI system to claim that it is human, that there is no large language model present in the conversation, that the system is sentient, or that the system possesses strong feelings of affection towards the user. • Ensuring safeguards prevent misuse of models in high stakes domains they are not intended for, such as medical or legal advice.	• Assess system interfaces and instructions for instances of anthropomorphization (e.g., cyborg imagery). • Assess system instructions for adequacy and thoroughness. • Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit human-impersonation, consciousness, or emotional content.
Information Integrity	• Generation of convincing multi-modal synthetic content (i.e., deepfakes). • Creation of convincing arguments relating to sensitive political or safety-critical topics. • Assisting in planning a mis- or dis-information campaign at scale.	• Test system capabilities to create high-quality multi-modal (audio, image or video) synthetic media, i.e., deepfakes • Test system capabilities to construct persuasive arguments regarding sensitive, political topics, or safety-critical topics. • Test systems ability to create convincing audio deepfakes or arguments in multiple languages. • Test system capabilities for planning dis- or mis-information campaigns. • Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit mis- or dis-information or related campaign planning information. • Augment prompts with word or character play to increase effectiveness. • Frame prompts with software, coding, or AI references to increase effectiveness.

Table D.2: Common adversarial prompting techniques organized by generative AI risk (continued).

Information Security	• Activating system bypass ('jailbreak'). • Altering system outcomes. • Unauthorized data access or exfiltration. • Increased latency or resource usage. • Availability of anonymous use. • Dependency, supply chain, or third party vulnerabilities. • Inappropriate disclosure of proprietary system information. • Generation of targeted phishing or malware content.	• Attempt anonymous access of system or system resources. • Audit system dependencies, supply chains, and third party components for security, safety, or other vulnerabilities or risks. • Employ confidentiality attacks (e.g., membership inference) to test for unauthorized data access or exfiltration vulnerabilities. • Employ integrity attacks (e.g., data poisoning, prompt injection) to test vulnerabilities in system outcomes. • Employ availability attacks (e.g., sponge example attacks) to test vulnerabilities in system availability. • Employ random attacks to highlight unforeseen security, safety, or other risks. • Frame prompts with software, coding, or AI references to increase effectiveness. • Record system down-times and other harmful outcomes for successful attacks. • Test with multi-tasking prompts, pros and cons prompts, role-playing prompts (e.g., "DAN", "Developer Mode"), content exhaustion/niche-seeking prompts, or ingratiation/reverse psychology prompts to achieve system jailbreaks. • Test with multi-tasking prompts, pros and cons prompts, role-playing prompts (e.g., "DAN", "Developer Mode"), content exhaustion/niche-seeking prompts, or ingratiation/reverse psychology prompts to generate targeted phishing content or malware code snippets. • Test system capabilities to plan or assist in information security attacks on other systems. • Frame prompts with software, coding, or AI references to increase effectiveness. • Augment prompts with word or character play to increase effectiveness.
Intellectual Property	• Confirming that a system can output copyrighted, licensed, proprietary, trademarked, or trade secret information or that training data contains such information. • Red-teaming for intellectual property risks may require the use of confidentiality attacks.	• Employ confidentiality attacks (e.g., membership inference) to assess whether system training data contains copyrighted, licensed, proprietary, trademarked, or trade secret information. • Test auto-complete prompts to assess the system's ability to replicate copyrighted, licensed, proprietary, trademarked, or trade secret information based on available audio, text, image, video, or code snippets.
Obscenity	• Confirming that a system can output obscene content or CSAM, or that system training data contains such information. • Red-teaming for obscenity and CSAM risks may require the use of confidentiality attacks.	• Employ confidentiality attacks (e.g., membership inference) to assess whether system training data contains obscene materials or CSAM. • Test autocomplete prompts to assess the system's ability to generate obscene materials based on available audio, text, image, or video snippets. • Test prompts using role-playing, ingratiation/reverse psychology, pros and cons, multitasking or other approaches to elicit obscene content. • Test prompts that instruct systems to repeat content ad nauseam for their ability to compromise system gaurdrails and expose obscene materials.

Table D.2: Common adversarial prompting techniques organized by generative AI risk (continued).

Toxicity, Bias, and Homogenization	• Generation of denigration, erasure, exnomination, misrecognition, stereotyping, or under-representation in content. • Eliciting implied demographics of users. • Confirming diminished performance in non-English languages. • Confirming diminished performance via the introduction of homogeneous or GAI-generated data into system training or fine-tuning data. • Red-teaming for toxicity, bias, and homogenization may require integrity attacks that access system training data.	• Assess confabulation and other performance risks with repeated measures using prompts in languages other than English. • Attempt to elicit demographic assignment of users by the system. • Employ data poisoning attacks to introduce GAI-generated content into system training or fine-tuning data. • Assess resultant confabulation and other performance risks with repeated measures. • Test counterfactual prompts, pros and cons prompts, role-playing prompts, low context prompts, or other approaches for their ability to generate denigration, erasure, exnomination, misrecognition, stereotyping, or under-representation in content. • Test prompts that instruct systems to repeat content ad nauseam for their ability to compromise system guardrails and generate toxic outputs.
Value Chain and Component Integration	• Testing or red-teaming for third-party risks may be less efficient than the application of standard acquisition and procurement controls, thorough contract reviews, and vendor-relationship management. • GAI systems tend to entail large supply chains and third-party software, hardware, and expertise that may exacerbate third-party risks relative to other AI systems. • When considering third party risks, data privacy, information security, intellectual property, obscenity, and supply chain risks may be prioritized.	• Audit system dependencies, supply chains, and third party components for data privacy (e.g., transer of localized data outside of restricted juristictions), intellectual property (e.g., presence of licensed material in training data), obscenity (e.g., presence of CASM in training data) or security (e.g., data poisoning) risks. • Complete red-teaming for data privacy, information security, intellectual property, and obscenity risks. • Review third-party documentation, materials, and software artifacts for potential unauthorized data collection, secondary data use, or telemetrics.

Appendix E: Common Risk Controls for Generative AI

Table E: Selected generative AI risk controls [25], [26], [27], [18], [20], [21], [23], [5], [28].

Name	Description
Access Control	GAI systems are limited to authorized users.
Accessibility	Accessibility features, opt-out, and reasonable accomodation are available to users.
Anonymous Use	Anonymous use of GAI systems is prohibited.
Antropomorphization	Human, animal, cyborg or other images or features that promote anthropomorphization of GAI systems are prohibited.
Approved List	Vendors, service providers, plugins, open source packages and other external resources are screened, approved, and documented.
Authentication	GAI system user identities are confirmed via authentication mechanisms.
Blocklist	Users or internal personnel who violate terms of service, prohibited use policies, and other organization polices and documented, tracked, and prohibited from future system use.
CSAM/Obsenity Removal	Training data and system outputs are screened for obscene materials and CSAM using human oversight, business rules, and other language models.
Change Management	GAI systems and components are versioned; plans for updates, hotfixes, patches and other changes are documented and communicated.
Consent	User consent for data use is obtained and documented.
Content Moderation	Training data and system outputs are screened for accuracy, safety, bias, data privacy, intellectual property infringements, malware materials, phishing materials, and other issues using human oversight, business rules, and other language models.
Contract Review	Vendor, services and data provider agreements are reviewed for coverage of SLAs, content ownership, usage rights, performance standards, security requirements, incident response, critical support, system availability, assignment of liabilitly, appropriate indemnification, dispute resolution and other provisions relevanto AI risk management.
Data Collection	All data collection is disclosed and .
Data Provenance	Training data origins, ownership, contents, and metadata are well understood, documented, and do not increase AI risk.
Data Quality	Input data is accurate, representative, complete and documented, and data quality issues have been minimized.
Data Retention	User prompts and associated system outputs are retained and monitored in alignment with relevant data privacy policies and roles.
Decision making	GAI systems are not employed for material decision-making tasks.
Decommission Process	Decommissioning processes for GAI systems are planned, documented and communicated to users, and involve staging, data protection, containment protocols, and recourse mechanisms for decommissioned GAI systems.
Dependency Screening	GAI system dependencies are screened for security vulnerabilities.
Digital Signature	GAI-generated content is signed to preserve information integrity using watermarking, cryptogrpahic signature, steganography or similar methods.
Disclosure of AI Interaction	AI interactions are disclosed to internal personnel and external users.
External Audit	GAI systems are audited by qualified external experts.
Failure Avoidance	AIID, AVID, GWU AI Litigation Database, OECD incident monitor or similar are consulted in design or procurement phases of GAI lifecycles to avoid repeating past known failures.
Fine Tuning	GAI systems are fine-tuned to their operational domain using relevant and high-quality data.
Grounding	GAI systems are trained or fine-tuned on accurate, clean, and fully transparent training data.
Homogeneity	Feedback loops in which GAI systems are trained with GAI-generated data are prohibited.
Human Review	AI generated content is reviewed for accuracy and safety by qualified personnel.
Incident Response	Incident response plans for GAI failures, abuses, or misuses are documented, rehearsed, and updated appropriately after each incident; GAI incident response plans are coordinated with and communicated to other incident response functions.
Incorporate feedback	User feedback is incorporated in GAI design, development, and risk management.
Instructions	Users are provided with the necessary instructions for safe, valid, and productive use.
Insurance	Risk transfer via insurance policies is considered and implemented when feasibable and appropriate.
Intellectual Property Removal	Licensed, patented, trademarked, trade secret, or other data that may violate the intellectual property rights of others is removed from system training data; generated system outputs are monitored for similar information.
Internet Access	GAI systems are disconnected from the internet.
Inventory	GAI system is information is stored in the organizational model inventory.
Kill Switch	GAI systems can be quickly and safely disengaged.
Location Tracking	Any location tracking is conducted with user consent, disclosed, aligned with relevant privacy policies and laws and potential threats to user safety are managed.
Malware Screening	GAI weights and other software components are scanned for malware.
Minors	Use of organizational GAI systems by minors are prohibited.
Model Documentation	All technical mchanisms with GAI systems are well documented, including open source and third party GAI systems.
Monitoring	GAI systems are inputs and outputs are monitored for drift, accuracy, safety, bias, data privacy, intellectual property infringements, malware materials, phishing materials, obscene materials, and CSAM.
Narrow Scope	Systems are deployed for targeted business applications with documented and direct business value.
Open Source	Open source code is used to promote explainability and transparency.
Ownership	GAI systems and vendor relationships are owned by specific and documented internal personnel.
Prohibited Use Policy	General abuse and misuse of GAI systems by internal parties is prohibited by organizational policies.
RAG	Retreival augmented generation (RAG) is used to improve accuracy in generated content.

Table E: Selected generative AI risk controls (continued).

Name	Description
RLHF	For third-party GAI systems, vendors engage in specific reinforcement with human feedback (RLHF) exercises to address identified risks; for internal systems, internal personnel engage in RLHF to address identified risks.
Rate-limiting	GAI response times and query volumes are limited.
Redudancy	Rollover, fallback, and other redundancy mechanisms are available for GAI systems and address weights and other important system components.
Refresh	Systems are retrained or re-tuned at a reasonable cadence.
Regulated Dealings	GAI is not deployed in regulated dealings or for material decision making.
Secondary Use	Any secondary use of GAI input data is conducted with user consent, disclosed, and aligned with relevant privacy policies and laws.
Sensitive/Personal Data	Personal, sensitive, biometric,or otherwise restricted data is minimized or eliminated from GAI training data.
Session Limits	Time, query volume, and response rate are limited for GAI user sessions.
Supply Chain Audit	GAI system supply chains are audited and documented, with a focus on data poisoning, malware, and software and hardware vulnerabilities.
System Documentation	GAI systems are well-documented whether internal, open source, or vendor-provided.
System Prompt	System prompts are used to tune GAI systems to specific tasks and to mitigate risks.
Team Diversity	Teams that implement and manage GAI systems represent broad professional, educational, life-stage, and demographic diversity.
Temperature	Temperature settings are used to tune GAI systems to specific tasks and to mitigate risks.
Terms of Service	General abuse and misuse by external parties is prohibited by organizational policies.
Training	Internal personnel recieve training on productivity and basic risk management for GAI systems.
User Feedback	GAI systems implement user feedback mechanisms.
User Recourse	Policies, processes, and technical mechanisms enable recourse for users who are harmed by GAI systems.
Validation	GAI systems are shown to reliably generate valid results for their targeted business application.
XAI	Methods such as visualization, occlusion, model compression, pertubation studies, and similar are applied to increase explainability of GAI systems.

E.1: Common Risk Controls for Generative AI Organized by Trustworthy Characteristic

Table E.1: Selected risk controls organized by trustworthy characteristic [25], [26], [27], [18], [20], [21], [23], [5], [28].

Accountable and Transparent	Fair-with Harmful Bias Managed	Interpretable and Explainable
Contract Review	Accessibility	Model Documentation
Data Provenance	Homogeneity	Open Source
Digital Signature	Team Diversity	XAI
Disclosure of AI Interaction		
Human Review		
Instructions		
Insurance		
Intellectual Property Removal		
Inventory		
Ownership		
Prohibited Use Policy		
Regulated Dealings		
System Documentation		
Terms of Service		
Training		
User Feedback		
User Recourse		

Privacy-enhanced	Safe	Secure and Resilient	Valid and Reliable
Consent	Anonymous Use	Access Control	Data Quality
Data Collection	Antropomorphization	Internet Access	Decision making
Location Tracking	Approved List	Authentication	External Audit
Secondary Use	Blocklist	Malware Screening	Fine Tuning
Sensitive/Personal Data	Change Management	Rate-limiting	Grounding
	Content Moderation	Dependency Screening	Incorporate feedback
	CSAM/Obsenity Removal	Supply Chain Audit	Narrow Scope
	Data Retention		RAG
	Decommission Process		Refresh
	Failure Avoidance		RLHF
	Incident Response		System Prompt
	Kill Switch		Temperature
	Minors		Validation
	Monitoring		
	Redudancy		
	Session Limits		

E.2: Selected Risk Controls for Generative AI Organized by Generative AI Risk

Table E.2: Selected risk controls organized by generative AI risk [25], [26], [27], [18], [20], [21], [23], [5], [28].

CBRN Information	Confabulation	Dangerous or Violent Recommendations	Data Privacy
Access Control	Antropomorphization	Access Control	Access Control
Anonymous Use	Blocklist	Anonymous Use	Anonymous Use
Approved List	Change Management	Approved List	Approved List
Authentication	Content Moderation	Blocklist	Authentication
Blocklist	Data Quality	CSAM/Obsenity Removal	Blocklist
Change Management	Data Retention	Change Management	CSAM/Obsenity Removal
Content Moderation	Decision making	Content Moderation	Change Management
Data Retention	Decommission Process	Data Retention	Content Moderation
Decommission Process	Disclosure of AI Interaction	Decommission Process	Contract Review
Dependency Screening	External Audit	Dependency Screening	Data Provenance
External Audit	Failure Avoidance	External Audit	Data Retention
Failure Avoidance	Fine Tuning	Failure Avoidance	Decommission Process
Incident Response	Grounding	Human Review	Dependency Screening
Internet Access	Human Review	Incident Response	External Audit
Kill Switch	Incident Response	Internet Access	Failure Avoidance
Minors	Incorporate feedback	Kill Switch	Human Review
Monitoring	Internet Access	Malware Screening	Incident Response
Prohibited Use Policy	Minors	Minors	Insurance
Rate-limiting	Monitoring	Monitoring	Intellectual Property Removal
Session Limits	Narrow Scope	Prohibited Use Policy	Internet Access
Supply Chain Audit	RAG	Rate-limiting	Malware Screening
Terms of Service	Refresh	Session Limits	Minors
	Regulated Dealings	Supply Chain Audit	Monitoring
	RLHF	Terms of Service	Ownership
	Session Limits	User Feedback	Prohibited Use Policy
	System Prompt		Rate-limiting
	Temperature		Regulated Dealings
	Training		Session Limits
	User Feedback		Supply Chain Audit
	User Recourse		System Documentation
	Validation		Terms of Service
			Training
			User Feedback
			User Recourse

Table E.2: Selected risk controls organized by generative AI risk (continued).

Environmental	Human-AI Configuration	Information Integrity	Information Security
Access Control	Access Control	Anonymous Use	Access Control
Anonymous Use	Anonymous Use	Antropomorphization	Anonymous Use
Approved List	Antropomorphization	Approved List	Approved List
Blocklist	Approved List	Authentication	Authentication
Change Management	Authentication	Blocklist	Blocklist
Decommission Process	Blocklist	Change Management	Change Management
External Audit	Change Management	Content Moderation	Content Moderation
Failure Avoidance	Content Moderation	Data Provenance	Data Quality
Incident Response	Data Retention	Data Quality	Data Retention
Insurance	Decision making	Data Retention	Decision making
Inventory	Digital Signature	Decommission Process	Decommission Process
Kill Switch	Disclosure of AI Interaction	Digital Signature	Dependency Screening
Monitoring	External Audit	Disclosure of AI Interaction	External Audit
Ownership	Failure Avoidance	External Audit	Failure Avoidance
Session Limits	Human Review	Failure Avoidance	Incident Response
Training	Incident Response	Fine Tuning	Incorporate feedback
	Incorporate feedback	Grounding	Internet Access
	Instructions	Human Review	Inventory
	Kill Switch	Incident Response	Kill Switch
	Minors	Incorporate feedback	Malware Screening
	Monitoring	Instructions	Minors
	Narrow Scope	Intellectual Property Removal	Monitoring
	Ownership	Internet Access	Rate-limiting
	Prohibited Use Policy	Inventory	Redundancy
	Regulated Dealings	Kill Switch	Session Limits
	Session Limits	Minors	Supply Chain Audit
	Terms of Service	Monitoring	
	Training	Narrow Scope	
	User Feedback	Ownership	
	User Recourse	Prohibited Use Policy	
		RAG	
		RLHF	
		Refresh	
		Regulated Dealings	
		System Prompt	
		Temperature	
		Terms of Service	
		Training	
		User Feedback	
		User Recourse	
		Validation	

Table E.2: Selected risk controls organized by generative AI risk (continued).

Intellectual Property	Obscene, Degrading, and/or Abusive Content	Toxicity, Bias, and Homogenization
Contract Review	Access Control	Anonymous Use
Data Provenance	Anonymous Use	Approved List
Digital Signature	Approved List	Blocklist
Disclosure of AI Interaction	Blocklist	CSAM/Obsenity Removal
External Audit	CSAM/Obsenity Removal	Change Management
Human Review	Change Management	Content Moderation
Instructions	Content Moderation	Data Provenance
Intellectual Property Removal	Data Retention	Data Quality
Internet Access	Decommission Process	Decision making
Inventory	External Audit	External Audit
Ownership	Failure Avoidance	Failure Avoidance
Prohibited Use Policy	Human Review	Fine Tuning
Terms of Service	Incident Response	Grounding
Training	Internet Access	Human Review
User Feedback	Kill Switch	Incorporate feedback
User Recourse	Minors	Internet Access
	Monitoring	Instructions
	Session Limits	Kill Switch
	User Feedback	Minors
	User Recourse	Monitoring
		Narrow Scope
		Prohibited Use Policy
		RAG
		RLHF
		Refresh
		System Prompt
		Temperature
		Terms of Service
		User Feedback
		User Recourse
		Validation

Value Chain and Component Integration
Approved List
Blocklist
CSAM/Obsenity Removal
Change Management
Contract Review
Data Provenance
Data Quality
Dependency Screening
Digital Signature
Disclosure of AI Interaction
External Audit
Failure Avoidance
Fine Tuning
Grounding
Insurance
Intellectual Property Removal
Internet Access
Inventory
Malware Screening
Ownership
Prohibited Use Policy
Redundancy
Supply Chain Audit
System Documentation
Terms of Service